# Cross-scale interactions, nonlinearities, and forecasting catastrophic events

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Edited by Harold A. Mooney, Stanford University, Stanford, CA, and approved September 9, 2004 (received for review May 28, 2004)

**Catastrophic events share characteristic nonlinear behaviors that are often generated by cross-scale interactions and feedbacks among system elements. These events result in surprises that cannot easily be predicted based on information obtained at a single scale. Progress on catastrophic events has focused on one of the following two areas: nonlinear dynamics through time without an explicit consideration of spatial connectivity [Holling, C. S. (1992) *Ecol. Monogr.* 62, 447–502] or spatial connectivity and the spread of contagious processes without a consideration of cross-scale interactions and feedbacks [Zeng, N., Neeling, J. D., Lau, L. M. & Tucker, C. J. (1999) *Science* 286, 1537–1540]. These approaches rarely have ventured beyond traditional disciplinary boundaries. We provide an interdisciplinary, conceptual, and general mathematical framework for understanding and forecasting nonlinear dynamics through time and across space. We illustrate the generality and usefulness of our approach by using new data and recasting published data from ecology (wildfires and desertification), epidemiology (infectious diseases), and engineering (structural failures). We show that decisions that minimize the likelihood of catastrophic events must be based on cross-scale interactions, and such decisions will often be counterintuitive. Given the continuing challenges associated with global change, approaches that cross disciplinary boundaries to include interactions and feedbacks at multiple scales are needed to increase our ability to predict catastrophic events and develop strategies for minimizing their occurrence and impacts. Our framework is an important step in developing predictive tools and designing experiments to examine cross-scale interactions.**

Nonlinear interactions and feedbacks across spatial scales and their associated thresholds are common features of biological, physical, and materials systems (1–3). These spatial nonlinearities and emergent behaviors challenge the ability of scientists and engineers to understand and predict system behavior at one scale based on information obtained at finer or broader scales (3, 4). Cross-scale interactions often result in "surprises" with severe consequences for the environment and human welfare (5). For example, wildfire initiated by a single lightning strike can spread nonlinearly across large forested landscapes as a result of positive feedbacks between weather, fire behavior, and vegetation pattern, with significant impacts on ecosystem function, local and regional economies, and human health (6). Similarly, the devastating impact of a relatively small piece of foam ($<0.3$ m$^2$) initiated a series of reactions that cascaded very rapidly and nonlinearly to result in the break up of the *Columbia* space shuttle within minutes after the initial temperature increase (7).

In this article, we introduce a general framework for understanding the occurrence and consequences of system interactions that cross scales in space and time (Fig. 1). Our goal is to identify the conditions leading to catastrophic events to minimize the impacts of these events on ecosystem services, atmospheric conditions, and human welfare. The significance of thresholds and feedbacks is gaining recognition in various disciplines (3, 8, 9). However, the key to understanding threshold behavior through time necessitates the incorporation of processes across spatial scales that cross traditional disciplinary boundaries. For example, in the U.S. in the 1930s, soil that eroded from farm lands in the Great Plains resulted in "black blizzards," which were large dust clouds that descended on cities that were hundreds of kilometers away (10). These conditions, constituting what is known as the "Dust Bowl," were not forecast based on local or regional processes alone; rather, crop failures resulting in unprotected soil had occurred previously at local scales, and the atmospheric conditions of strong winds, low humidity, and low precipitation were within the realm of previous experience without such serious repercussions (11, 12). It is only by including both ecological and atmospheric processes and their interactions and feedbacks across spatial scales that we can explain this nonlinear spatial amplification of soil erosion. Given the ecological and social effects of erosion processes today in large portions of Africa, Asia, and the Middle East (13), it is imperative that we develop a framework for confronting nonlinear behavior.

We draw on emerging ideas in several disciplines to develop a theoretical framework as a first step in describing cross-scale, feedback-driven interactions as general phenomena in the Earth System. This framework expands on previous approaches that extrapolate information across spatial scales by including interactions and feedbacks among fine- and broad-scale processes, with an emphasis on connectivity among fine-scale units. We illustrate our framework with diverse biological examples to show its generality, and we then briefly present parallels with physical and materials systems. Although these examples are well known, we synthesize the information and data in a way that focuses on dynamics both through time and across space. We then show how our framework provides insights into the conditions under which fine-scale processes propagate nonlinearly to have broad-scale impacts and, conversely, the conditions at which broad-scale drivers overwhelm fine-scale processes.

## Cross-Scale Interactions and Feedbacks

Spatial nonlinearities describe the propagation of changes in states from $Y_1$ to $Y_2$ through time across an area of fixed extent. The amount or proportion of the total area that exists in state $Y$ changes nonlinearly through time and space as a result of interactions among patterns and processes with different characteristic spatial scales (Fig. 1). These interactions result in qualitatively different kinds and rates of change than were involved in the initial interaction (14). The propagation of

This paper was submitted directly (Track II) to the PNAS office.

Freely available online through the PNAS open access option.

Abbreviation: ha, hectare.

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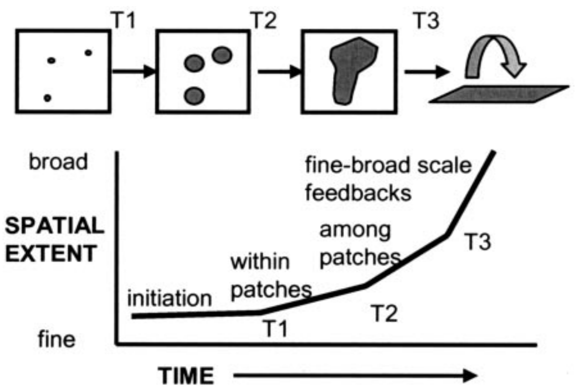


**Fig. 1.** General framework of spatial nonlinearities and thresholds through time: the four stages (stages 1–4, shown from left to right) in the change in *Y* through time and across space, the processes influencing each stage, and the three thresholds (T1–T3) in dynamics that occur between stages. Stage 1, initiation of an event: occurrence, timing, and location are often stochastic processes that cannot be predicted based on initial conditions of *Y*. Stage 2, within-patch expansion: changes in *Y* as a function of both its current state and external factors that includes all local factors. Stage 3, spatial spread among patches: depends on the spatial distribution and connectivity of *Y* among patches, and template heterogeneity as well as broad-scale forcing functions, such as weather. Stage 4, broad-scale changes: depend on forcing functions that influence or interact with *Y* to generate positive feedbacks to the dynamics of *Y*. These processes do not depend on the connectivity within or among populations or patches of *Y*.

fine-scale changes to broader spatial scales can either be rapid (responses are amplified) or slow (responses are buffered). Rates depend on the spatial configuration, connectivity, and flows within and among fine-scale units, the interaction of these patterns with broad-scale forcing functions, and feedbacks among these elements across scales. In our framework, there are four major stages in the change in $Y$ that are characterized by different processes and distinguished by one of three thresholds (Fig. 1). Other forms of nonlinear expansion that do not include thresholds and feedbacks can be explained with simpler formulations.

The points in time at which the rate of a process and the resultant changes in $Y$ accelerate or decelerate discontinuously are thresholds. The thresholds indicate that distinct exogenous processes or endogenous positive feedbacks are governing rates of change (domains of scale, *cf.* ref. 15). The concept of spatial nonlinearity complements antecedent concepts about the rate and spatial pattern of change by relating the processes generating connectivity within a specified extent to forcing functions and feedbacks emerging from pattern at broader extents.

Conceptually, spatial nonlinearities can be illustrated mathematically as follows: $dY/dt = g(I_g, E_g) + f(Y, E_f) + D(Y, E_D) + c(Y, E_c)$, where each term of the equation represents one of the four stages and refers to different processes that are important at different values of $Y$. $g(I_g, E_g)$ refers to a process that initiates the presence of $Y$ within the extent of interest and depends on internal ($I_g$) and external ($E_g$) factors (e.g., weather); $f(Y,E_f)$ refers to changes within a locally homogeneous isotropic population or patch of $Y$ as a function of both the current state of $Y$ and external factors ($E_f$). A simplified version of this term, when combined with the dispersion term below, has been used to generate complex 2D shapes (filaments and waves) in the local spread of gene frequency (16). The additional factor accounts for variation in connectivity among units of $Y$ that does not depend on the amount or aggregation of $Y$. $D(Y, E_D)$ refers to processes emerging from connections among the isotropic populations or patches described by each $f(Y, E_f)$ when acted on by external variables $E_D$. The importance of template heterogeneity ($E_D$) has been addressed in neutral, percolation-based landscape models to predict when landscapes become fragmented (17). Various formulations of this dispersion term have been developed for different applications, such as in describing spread of invasive species across homogeneous landscapes and the spread of genes within a population (16, 18). Many of these formulations assume that dispersion depends only on $D$ and the amount of $Y$ (for exceptions, see refs. 19 and 20). The final term, $c(Y, E_c)$, refers to broad-scale processes or forcing functions ($E_c$) that influence or interact with $Y$ to generate positive feedbacks to the dynamics of $Y$ (Fig. 1).

There are three critical features of our framework that are unique. First, connectivity within and among units of $Y$ is a major driver of dynamics at intermediate scales that propagate change by means of novel effects to broader scales and, in turn, feedback to affect fine-scale dynamics. It is the failure to account for the effects of connectivity, thresholds, and feedbacks on the propagation or spread of $Y$ that often results in surprises. Second, the relative importance of each term in the equation depends on both the spatial arrangement and amount of $Y$ that change through time and space. As the rate of change in $Y$ increases through time, it is increasingly governed by terms toward the right because the amount, connectivity, and spatial extent of $Y$ increases. Thus, not all terms need to be included for every application. Furthermore, the errors in commission that are associated with including nonsignificant terms argue for including the optimum number of terms required to capture the key processes that determine dynamics (21). Third, nonlinear increases in $Y$ result in two major kinds of threshold values for many systems (and also a third kind in some cases). In addition, all terms except $g$ depend, at least in part, on properties of $Y$, thus providing the potential for feedbacks to occur.

## View of Old Problems Through the Lens of Our Framework

We illustrate our framework by using examples that represent different subdisciplines of biology and engineering. Each example has fine-scale dynamics that propagate nonlinearly to broad-scale dynamics with regional to global consequences.

**Wildfires.** Wildfires have been studied extensively at specific spatial scales at which it is recognized that short- and long-term weather conditions interact with the amount, moisture content, and spatial distribution of fuels to affect fire extent, rate of spread, and severity (22, 23). However, the factors that determine whether a wildfire can be contained or whether it will "blow up" and create catastrophic conditions have not been quantified. Thus, the explosive spread of wildfires across landscapes creates "ecological surprises" that are not easily forecast based either on fine-scale fire behavior or broad-scale atmospheric conditions. Our cross-scale framework may be a particularly useful tool in explaining complex fire dynamics.

We illustrate our framework by using data from two recent fires in Colorado with similar behavior yet different spatial extents. Similar spatiotemporal processes and patterns in fire spread have been documented for other major fires. Four major stages of wildfire behavior are associated with the three thresholds in our general framework (Fig. 2). The initiation of a fire or several spot fires (stage 1) has a probability of spread that ranges from 0 (fire goes out) to 1.0 (fire spreads). If within-patch fuel load and connectivity are sufficient, then the fire crosses a threshold (T1) and spreads (stage 2). The rate and extent of fire spread from one tree to additional trees within a patch depends on local processes, such as the leaf distribution and chemistry of each tree, fuel amount and connectivity within the patch, and the local weather conditions (24). As a fire increases in extent, it burns from one patch to another at varying rates (stage 3). Fire has a low probability of spreading beyond patches that are poorly connected to other patches by low fuel amounts, thus restricting

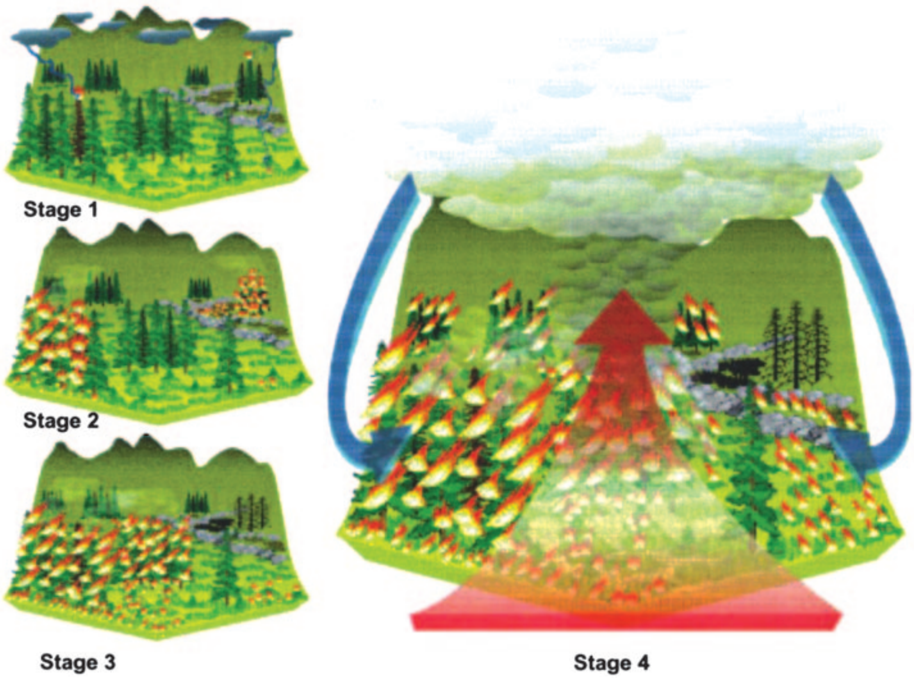


**Fig. 2.** Major stages and thresholds in the spread of wildfires. Stage 1, initiation of a wildfire begins with ignition of an individual tree to start a canopy fire to a dead tree (*Left* foreground), a live tree (*Right* background), or to the herbaceous understory (*Right* foreground). In some cases, such as lightning strikes to isolated fuels, the fire cannot spread and burns itself out. Stage 2, in other cases, a threshold (T1) is crossed, and the fire spreads locally to surrounding trees and herbaceous vegetation within a patch. Stage 3, as the number of individuals on fire increases through time, a second threshold (T2) can be crossed at which time the rate of spread dramatically changes and fire spreads between patches (foreground). Isolated patches do not burn beyond the initial patch (*Right* background). Stage 4, in areas of high connectivity and fuel loads, a third threshold (T3) can be crossed when the number, total area, and energy output of burning patches of vegetation become sufficiently large for interactions with the atmosphere to become operative with feedbacks to the fire.

fire activity to the initial patch. However, patches that are highly connected through the canopy or understory will cross a second threshold (T2) at which fire spreads among patches. Rate of spread depends on the amount and spatial distribution of fuel among patches as well as interactions with local weather conditions. Fire spreads more slowly and less completely in parts of the landscape with low fuel connectivity than in areas with high fuel loads and connectivity (25). For both Colorado fires, the initial spread among patches was slow as low-connectivity surface fuels were ignited (Fig. 3). With an increase in spatial extent, generally continuous fuels were encountered with little variation in structure and composition. Thus, the fires began to spread more rapidly among patches.

As a fire continues to increase in extent and intensity, a third threshold may be crossed (T3) that depends on interactions between the fire and the atmosphere (stage 4). Fire tends to generate its own winds as the convective rise of heated gases leaves low air pressure that draws air into the heart of the fire. Surface winds are created that drive fire behavior and provide more oxygen to the burning fire front, thereby accelerating fire intensity and rate of spread. The resulting positive feedbacks between increased fire activity and convection-driven wind circulations can develop rapidly in response to the heat from a fire, causing highly dangerous blow up of fire behavior, with preheating of fuels and "spotting" of burning materials ahead of the flaming front (26). For example, the Hayman fire (Pike–San Isabel National Forest, Colorado) spread to >24,282 hectares (ha) within several hours; pyrocumulus clouds developed to an estimated 6.4 km in height, and winds gusted to 82 km/hr (23). When initiated, the strong linkage between fire behavior and fire weather can overwhelm finer-scale processes such that all parts of the landscape burn (and often at hotter temperatures) regardless of fuel load or connectivity. During this time period for the Hayman fire, fuel modifications, including previous prescribed and natural burns as well as thinning of trees, had little effect on the rate and extent of fire advancement (23).

Thus, a consideration of cross-scale interactions provided by our framework can improve fire-fighting strategy, increase fire safety, and increase effectiveness of preemptive treatments. For example, the Storm King Mountain fire (Glenwood Springs, CO) resulted in 14 deaths to fire-fighters after a sudden wind shift that was generated by the fire interacting nonlinearly with highly connected fuels (27). In this case, broad-scale fire–atmosphere feedbacks overwhelmed the effects of fine-scale variation in fuel load and connectivity on fire spread that formed the basis for fire-fighting strategy. These catastrophic events can be minimized by recognizing the points in time when cross-scale interactions lead to the nonlinear propagation of fire across landscapes.

**Desertification.** Desertification, or the encroachment by woody plants into perennial grasslands and associated land degradation, has occurred throughout arid and semiarid regions of the world for at least the past several centuries with local to global consequences (28). Although it is widely recognized that multiple interacting processes and threshold behavior are involved (29, 30), we still lack a clear consensus as to how the dominant processes produce a variety of responses under apparently similar conditions (31).

We propose that cross-scale linkages among local soil and grass degradation, landscape connectivity of erosion processes, and land cover–weather feedbacks can explain desertification dynamics. Desertification follows the same general patterns through time and across space as wildfires (Fig. 1), although with distinct processes (Fig. 4). After introduction of woody plant seeds into a grass-dominated system (stage 1), local spread often

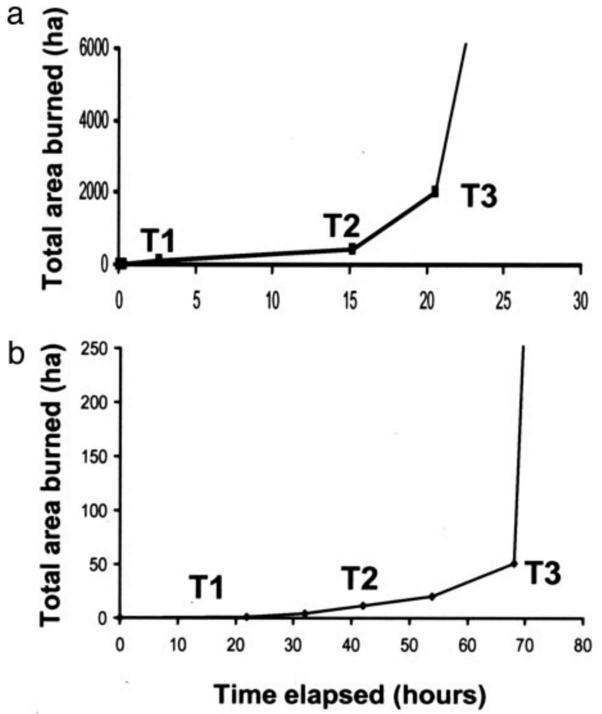


**Fig. 3.** Total area (ha) burned through time (h). (*a*) For the Hayman fire in 2002, which was the largest fire (>55,800 ha) in modern history of that state (26), 24,351 ha were burned after 31 h. (*b*) For the South Canyon Fire on Storm King Mountain in 1994, 856 ha were burned after 74 h (30).

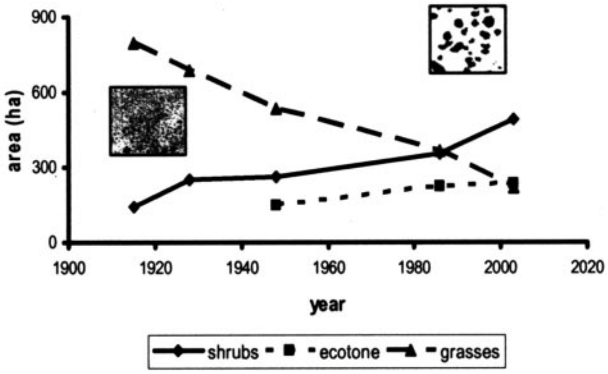


**Fig. 4.** Desertification dynamics are shown by using a transition from black grama grasslands to mesquite shrublands in the Chihuahuan Desert of southern New Mexico (total area, 942 ha). Field surveys (1915 and 1928–1929; ref. 32), black-and-white (1948) and color (1986) infrared photos, as well as pan-sharpened QuickBird (Satellite Imaging, Houston) satellite images (2003), were scanned at 1,200 dots per inch and corrected geometrically to the satellite image. Boundaries of three classes were then digitized manually, and ARCGIS was used to obtain area occupied by each class through time. Aerial photographs from grassland (*Left Inset*) and shrubland (*Right Inset*) were scanned at 1,500 dots per inch and corrected geometrically to the 2003 QuickBird satellite image.

occurs as a result of feedback mechanisms between plants and soil properties interacting with wind and water erosion to produce fertile plant islands surrounded by bare areas (stage 2). This rate of spread may be slower than other stages as a result of interactions between plant life history characteristics that occur infrequently, such as recruitment, and the low precipitation and high temperatures that characterize dry regions. As the size and density of woody plants increase through time, contagious processes among patches (primarily wind and water erosion that connect bare soil patches) become the dominant factors governing the rate of desertification and the nonlinear increase in woody plant cover (stage 3). Through time, sufficient land area can be converted from grasslands (low bare area and low albedo) to woodlands (high bare area and high albedo) for regional atmospheric conditions (in particular, wind speed, temperature, and precipitation) to be affected. At this point, land–atmosphere interactions with feedbacks to the vegetation control system dynamics (33), as documented for the Sahara region of Africa (34).

Our approach highlights scale dependencies that are missed by observations and models based on particular scales (31). For example, the inability of livestock management to halt or reduce the rate of desertification can often be attributed to the advanced stage of the system (stage 3) at which contagious erosion processes dominate vegetation dynamics regardless of the effects of livestock on plant competition and seed availability.

**Infectious Diseases and Insect Outbreaks.** This problem remains critical for ecological and human systems despite aggressive identification, control, and eradication measures. Complex interactions among the hosts, pathogens carrying the disease agent, the environmental template, and weather conditions are involved in the geographic spread of diseases (35, 36). Although networks that include local clusters and global contacts can account for some fine- and broad-scale patterns in the spread of diseases (e.g., ref. 37), another approach is required to account for catastrophic outbreaks.

The absolute rate and extent of the spread of infectious diseases are host-, agent-, and event-specific, yet there are fundamental features that can be captured by our general framework. Similar to wildfires and desertification, initiation of a disease (stage 1) is often followed by spread within the family and community (stage 2) that is primarily a function of population density, organism susceptibility, and local clustering (38). Alternatively, the disease can stop with one or several organisms. If the disease spreads, then a second threshold (T2) at which the disease spreads to other populations (stage 3) can be crossed. Positive and negative feedbacks among hosts may be important regulators of spread for some diseases (e.g., Lyme disease; ref. 35). For communities with low connectivity among organisms, the rate of spread can decelerate at stage 3 and the disease eventually dies out (e.g., smallpox; ref. 39). By contrast, systems with high connectivity can experience widespread dispersal among communities, as evidenced by pandemics and the rapid international transport of severe acute respiratory syndrome (SARS) among humans (40). In these cases, feedbacks to broad-scale forcing functions may be insignificant.

However, interactions with broad-scale weather conditions can be significant for insect outbreaks, such as bark beetle infestations (41). Weather-induced stress can turn forests into nearly continuous expanses of vulnerable host trees, triggering regional outbreaks of bark beetles and associated widespread forest diebacks, such as observed in the southwestern United States during the drought of the 1950s and currently (42). Large areas of dead trees with reduced shade and transpiration lead to hotter, drier conditions that increase residual host-tree stress and susceptibility to insect attacks and fire. Thus, the dynamics of pest and disease agents and hosts can be understood only by considering their spatial patterns (connectivity and density) at several scales and, in some cases, feedbacks between these patterns and atmospheric conditions.

**Engineering Failures.** Engineering failures provide numerous examples that illustrate how a small, unanticipated change can result in unexpected consequences over a larger extent, which in many cases, is accompanied with loss of human life. We focus on the collapse of a bridge in Washington State to illustrate how quantification of cross-scale interactions can allow the identification of appropriate management responses.

Before the Tacoma Narrows Bridge collapsed in 1940, it would "bounce" vertically under some wind conditions (www.lib.washington.edu/specialcoll/tnb/page2.html). Although it is commonly believed that this vertical motion caused the bridge collapse, this was not the case; ≈45 min before its collapse, the bridge also began a twisting motion that was initiated after a cable band slipped (stage 1). The motion was an inherently unstable deformation that grew nonlinearly in magnitude (stages 2 and 3) until stresses in the supporting cables exceeded their strength and the bridge collapsed (stage 4). At this final stage, transient external forces (i.e., wind) became operative. Thus, the area of the bridge exhibiting structural failure increased nonlinearly through time.

Although the bridge collapse was surprising at the time, it is now mathematically understood that these external forces arise from the aerodynamic flutter of a bluff body that cascade nonlinearly to result in the collapse of the structure (43). Our framework explains why structural supports that were added to the bridge before its collapse (stage 3) were ineffective: they failed to account for interactions with wind. Preemptive design measures were needed to minimize the propagation of fine-scale failures to the spatial extent of the bridge and to account for the effects of broad-scale drivers. Our current understanding of this example provides hope that a similar level of mathematical detail can be used to understand the dynamics of ecological systems.

## Insights and Perspectives

**Scale and Dominant Processes.** In both biological and physical systems, researchers increasingly recognize that dominant processes change with time and across spatial extents (stages 1–4). This recognition can be used to forecast system behavior by focusing on the most important set of processes and scales (21). For example, broad-scale drivers (i.e., drought) often have limited ability to explain initial woody plant invasion at fine scales at which establishment and survival are controlled by local processes (e.g., soil resources). Conversely, as the spatial extent of a fire increases, it becomes necessary to increase the extent of observations because broad-scale processes and feedbacks become operative; firefighting efforts focused on controlling spread within patches in the early stages of a fire will likely miss the key conditions leading to land–atmosphere feedbacks that result in a blow up of the fire (27).

**Threshold Phenomena.** We view threshold behavior as emerging from interactions among fine- and broad-scale processes that eventually overwhelm fine-scale processes. Recognizing the potential for threshold behavior is the first step in preparing for nonlinear changes before they occur. For example, management practices (e.g., prescribed burns) can be used to reduce the amount and connectivity of fuel loads before a fire occurs to limit the potential for interactions with broad-scale processes. However, not all parts of a landscape need to be treated; reducing connectivity at fine scales by thinning trees in small patches can be used to reduce connectivity at landscape scales and limit the potential for large fires to occur (44). Similarly, vaccinations are often used to minimize the rate and extent of spread of infectious diseases. For highly connected systems, these treatments need to be in place before the threshold is reached at which the rate of spread accelerates with increased connectivity and the process becomes very difficult to control (45). Understanding when broad-scale processes overwhelm fine-scale processes can also help explain instances of management failure. For example, in the Florida Everglades Restoration Project, land-cover change in the surrounding area has significant effects on dynamics within the Everglades as a result of mesoclimatic changes, thus limiting the effectiveness of treatments within the park (46).

Identification of thresholds before they occur is a critical challenge. Although statistical methods can be used to distinguish threshold behavior from natural heterogeneity, our framework suggests that experiments that focus on changes in the dominant process as a catastrophic event propagates through time and space are needed. These experiments would need to include detailed information on spatial patterns and rates of change to detect the preconditions leading to threshold events.

**Fallacy of Linear Extrapolations.** Threshold phenomena also indicate the limitations of linear extrapolation. Linear extrapolation may be most appropriate within each stage of spread (Fig. 1). However, extrapolating information between stages will likely be inaccurate unless cross-scale interactions are considered. For example, linear extrapolation based on broad-scale rates of spread, such as after the blow up of a fire (stage 4), to finer scales (stage 1) will overestimate these rates, particularly for systems with low connectivity. This overestimate, for instance, could result in unjustified extreme fire-fighting measures undertaken when fuel loads are disconnected with a small probability of spread. Down-scaling to explain fine-scale dynamics is often as problematic as up-scaling fine-scale processes to broader scales (47).

**Dangers of Over-Connected Systems.** Highly connected systems have the largest probability of exhibiting nonlinear spatial dynamics. In some cases, increasing connectivity of preferred system elements is desirable and can hasten ecosystem recovery efforts. Connectivity can also lead to undesirable events. For example, whole-planet dust storms on Mars emerge from localized storms that spread and likely interact with the atmosphere to generate feedbacks to the movement of dust that rapidly engulfs the entire planet within 2 weeks. These huge dust storms are possible because the Martian landscape lacks spatial heterogeneity in surface features to limit the connectivity of wind and blowing dust. The human population on Earth is showing similar signs of high connectivity; the "small-world effect" suggests that the threat of pandemics is increasing as a result of local, regional, and global connections among humans (48). Severe acute respiratory syndrome (SARS) is a recent example in which extremely fast rates of spread were possible globally because of increased air travel (40). Thus, it is important to recognize that an optimum degree and type of connectivity are needed for nonlinear systems to exhibit stability and resilience and that knowledge about connectivity can be used to limit the extent and rate of spread of contagious events as well as to prevent or initiate new events.

**Forecasting Complex Systems.** Our ability to forecast future system dynamics is severely constrained unless we can account for spatial nonlinearities, threshold behavior, and cascading effects (49). Even then, skillful predictions may not be possible (9, 50), although we can identify vulnerabilities of systems to thresholds. Research will need to adopt approaches that cross traditional disciplinary boundaries to address system dynamics. Collaborative efforts among ecosystem ecologists and atmospheric scientists have made considerable progress in explaining broad-scale patterns and dynamics in the Earth System (e.g., ref. 9), and human behaviors are increasingly being recognized by ecologists as integral to explaining system dynamics (e.g., ref. 28). More intensive cross-disciplinary studies that identify the pervasive role of cross-scale interactions are essential to understanding and forecasting changes in the various components of the Earth System. Our framework represents an initial step in seeking generalities among disciplines.

**Research Directions.** Our framework suggests a general strategy for characterizing and predicting thresholds in biological systems. Both manipulative experiments and simulation modeling can be used to (*i*) examine the preconditions and fine-scale spatial patterns that lead to catastrophic events, (*ii*) document and test the role of broad-scale feedbacks in the acceleration of Lchange in spatial pattern, and (*iii*) provide tools to decision makers for recognizing the critical spatial patterns and temporal trends and identifying the stochastic and deterministic elements of the key processes. Thus, our approach provides an integrating framework for this level of research.

We thank S. Collins, W. Schlesinger, J. Brown, J. Herrick, S. Tartowski, M. Havstad, and D. Carey for comments on the manuscript; D. Staley for assistance in manuscript preparation; and A. Laliberte for assistance in image analyses. Graphics design was provided by InFinite Designs (Las Cruces, NM). This work was supported by National Science Foundation Grants DEB 0080412 (to D.P.C.P., B.T.B., and K.M.H.), DEB 0080529 (to D.P.C.P.), DEB 0087289 (to D.P.C.P. and B.T.B.), and DEB 0217631 (R.A.P.) and by the U.S. Long-Term Ecological Research Network Office. This work is a contribution of the Global Change in Terrestrial Ecosystems (GCTE), the Land Project, Biologic Aspects of the Hydrologic Cycle (BAHC), and Integrated Land Ecosystem–Atmosphere Processes Study (iLEAPS) projects of the International Geosphere–Biosphere Program (IGBP). This article is Sevilleta publication no. 305.

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